Changepoints Detection in Social Networks: an Extension of Relational Event Model

RESEARCH REPORT

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Abstract

Detecting changepoints is crucial in the social network field to identify the time points when stimulus occur in the network, providing insight into the dynamic evolution of the network. This paper presents an approach that facilitates the detection of changepoints in social networks by combining changepoint detection algorithms with the Moving Window-Relational Event Model (MW-REM). The MW-REM is a social network model that predicts future events and accounts for factors that influence social interactions. To capture the dynamics of the influence levels of these factors over time, the MW-REM uses the Moving Window (MW) approach that models each fitted window to capture fluctuations in the effects' influence level. The approach suggested in this paper incorporates changepoint detection algorithms to detect sudden shifts in the influence levels of these factors using the parameters given by the MW. We conducted an evaluation of three changepoint detection algorithms - Binary Segmentation, Pruned Exact Linear Time, and Bayesian Online Changepoint Detection using synthetic data. To test the practical feasibility of our proposed method, we then applied these algorithms to analyze real-life Apollo-13 voice loop data. The approach can facilitate a better understanding of social dynamics, help identify potential challenges, and inform future strategies based on data.

Keywords:
Social network, Relational Event Model, Moving Window approach, Changepoints detection, Binary Segmentation, Pruned Exact Linear Time, Bayesian Online Changepoint Detection Method

1. Introduction

Changepoints are sudden shifts within the time series data which reflect the transitions occurring across conditions[30][3]. The detection of changepoints is essential in many domains. In the social network area, due to the rich dynamics of social networks, changepoint detection allows us to spot the time points when certain stimulus occurred in the network, such as traffic accidents, organizational interventions, etc., assisting us to observe the dynamic evolution of the network more clearly. However, research and applications of changepoint detection are relatively lacking in the social network field.

The aim of this study is to suggest an approach that facilitates detection of changepoints in social networks. To this end, we introduce changepoint detection methods into the structure of the relational event model (REM). The REM is a social network model that can predict the time and individuals involved in the future events in a social network. It is fitted in the relational event history (REH) data (Table 1), a social network data that at minimum contains information about the time, senders and receivers of events occurring in the social network. Generally, REM brings factors (e.g., gender, age, interaction inertia, etc.) that affect social interactions into the model through parameterization. Such factors are termed "effects"[7], and the parameters of the REM represent the influence level of each effect in the social network.

Time (hh, mm, ss)	sender	receiver	message
13:14:05	Patel	Chen	The weather conditions look good.
13:14:09	Chen	Patel	Yes, it should be a smooth flight.
13:14:12	Nguyen	Chen	I've done my safety checks.
13:14:14	Chen	Nguyen	Great job!

Table 1.: An Example of Relational Event History Data

However, the influence level of effects in REM is assumed to hold constant over time, which seems unrealistic considering the dynamic nature of real-life interactions. To address this limitation, Mulder and Leenders [24] proposed the Moving Window (MW) approach built upon the REM construct, which is capable of capturing the dynamics of the influence levels across time. The main concept of MW is to delineate specific duration of time (i.e. a window) that partially overlaps with the subsequent window and slides over the entire event history. Thereafter, by modeling each fitted window, we can model the fluctuations of the effects' influence level. The difficulty, however, is that the influence level typically varies between consecutive windows, leaving the visual identification of changepoints a challenge.

In this study, we introduce changepoint detection algorithms (CPDs) into the combined MW-REM framework. By feeding these algorithms (influence level) parameters along the windows, we enable researchers to discover changepoints across the REH. This can be employed on any social network scenario, such as: communication in the surgical room, interaction between teacher and students, as well as cooperation and competition between companies. The detection of changepoints can thus facilitate better understanding of social dynamics, help identify potential challenges as they appear and help inform future strategies based on data. Our study focuses specifically on the performance of three CPDs in the MW-REM structure: Binary Segmentation (BS), Pruned Exact Linear Time (PELT), and Bayesian Online Changepoint Detection (BOCPD). These methods were identified as top performers in a comparison conducted by van den Burg and Williams [11] in a general application. To evaluate their feasibility and performance in the context of social network scenarios within MW-REM, we utilize synthetic data to calculate metrics such as Confusion Matrix, Mean Squared Error (MSE), and Mean Signed Difference (MSD). We also apply these methods to real-life data to test their external validity. The blueprint of our study is depicted in Figure 1.

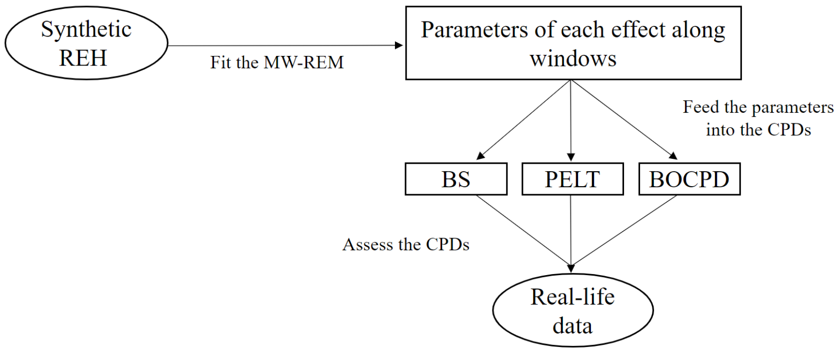

Figure 1.: Flowchart Depicting the Research Design of the Present Study

2. Methodology

2.1. *Moving Window-Relational Event Model (MW-REM)*

In this study, we utilized the Moving Window-Relational Event Model (MW-REM), a hybrid approach developed by Mulder and Leenders[24]. The MW-REM builds upon the Relational Event Model (REM) proposed by Butts[7] and overcomes its limitations by identifying changes in the effect parameters over time.

The REM is a powerful tool for modeling network data that contains sender, receiver, and time information, known as Relational Event History Data (REH). By analyzing the impact of various effects on the social network, the REM enables us to predict the next event in the network. This approach parameterizes both exogenous effects, which are actor characteristics that do not depend on past interactions in the network, such as age or gender, and endogenous effects, which depend on past interactions in the network, such as transitivity or inertia.

The REM considers every possible sender-receiver combination (s, r) in the network as a potential occurrence at time t, and the collection of these pairs at time t forms the risk set, denoted as $R(t)$. The risk set's size for each event is usually $N \times (N-1)$, where N refers to the number of actors in the social network, as each actor can only be either a sender or a receiver, but not both.

The REM models the event rate (λ) to predict which sender-receiver pair (s, r) will be involved in the next event and when it will occur. Each (s, r) pair is equipped with its own event rate for each event and is assumed to remain constant between the time of the present event and the time of the following event. The (s, r) pair with a higher event rate in the risk set R at time t is more likely to occur in the next event. The probability of the (s, r) pair taking place in the next event follows a multinomial distribution, which is given by:

$$P\left((s,r)|t\right) = \frac{\lambda(s,r,t)}{\sum_{R(t)} \lambda(s,r,t)} \tag{1}$$

, where $\lambda(s, r, t)$ represents the event rate of a pair (s, r) and $R(t)$ denotes the risk set for time t.

On the other hand, the duration between two events follows an exponential distribution, which is given by:

$$\Delta t \sim Exponential\left(\sum_{R(t)} \lambda(s,r,t)\right) \tag{2}$$

, where Δt denotes the duration between two events. The higher the total event rate of the risk set, the shorter the Δt.

The event rate is typically considered as a log-linear function of the outcome in REM with specific effects, given by:

$$\log \lambda(s, r, t) = \sum_{p} \beta_p x_p(s, r, t) \tag{3}$$

, where β_p represents the parameter of effects, which expresses the influence level of one effect on the entire social network, and $x_p(s, r, t)$ denotes the statistics, which can be either an exogenous or endogenous effects.

The REM can use event rate modeling to forecast the timing and participants of the next event. However, this method assumes a constant level of influence (i.e., β_p) for all effects throughout the event history, which is unrealistic in dynamic social interactions.

To address the limitations of REM, Mulder and Leenders proposed the Moving Window approach (MW) under the REM framework[24]. In this study, we refer to this approach as MW-REM. The MW-REM involves setting up a fixed-size window, i.e., a fixed length of time, that slides over the entire Relational Event History (REH) data. Each window shares a fixed-size overlap with the previous window, and the REM is fitted to each window (see Figure 2). This approach allows us to reveal the influence level of each effect on the social network over time through the parameters (i.e., β_p) given in each window. Additionally, it enables us to investigate social network dynamics over time, a feature not available in the original REM.

To better understand social network dynamics over time and detect significant changes in the network structure, we employ changepoint detection methods in the MW-REM framework.

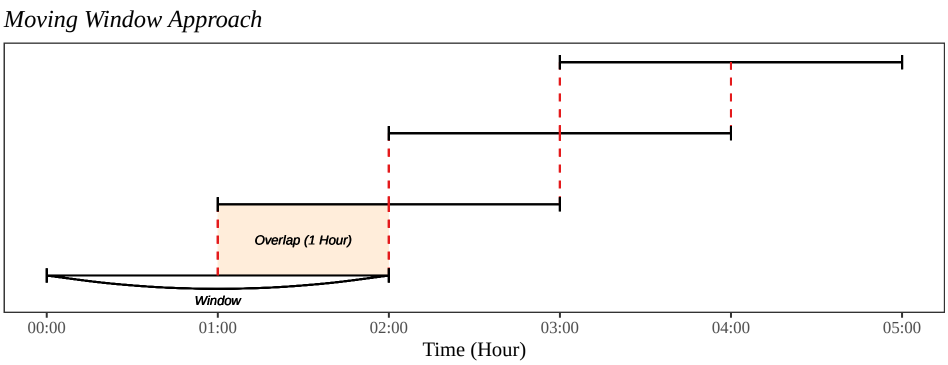

Figure 2.: An Example of Moving Window Approach

2.2. *Changepoint detection in the MW-REM*

In social network analysis, changepoints refer to significant changes in the underlying structure of a network over time. Detecting changepoints is crucial for identifying trends, patterns, and events that influence the evolution of social networks and for informing future strategies based on data. Despite its importance, there have been limited studies on inferring changepoints in the REM framework of the social network area. Shafiee Kamalabad suggested using Bayes Factor to infer changepoints on REH of a social network, which uses the support of two hypotheses from the data to prove the existence of changepoints [29]. However, apart from this study, there have been few studies on changepoint detection under the REM framework.

In this study, we propose a novel approach for detecting changepoints in REH, building on the foundation of MW-REM. As MW-REM divides the event history into partially overlapping sub-portions to fit the REM, it provides us with effect parameters (β_p) for each window over time, indicating the influence level of each effect during that period, as shown in Equation 3. By fitting MW-REM to the event history, we obtain as many REMs as the fitting windows, and therefore the same number of effect parameters (β_p) as the number of fitting windows.

Our proposed approach utilizes three CPDs for detecting changepoints in social networks: Binary Segmentation (BS), Pruned Exact Linear Time (PELT), and Bayesian Online Changepoint Detection (BOCPD). BS is an offline method that divides the data into smaller segments and iteratively tests for a changepoint in each segment. It is easy to implement and provides good results in practice. PELT is an online method that uses dynamic programming to search for the most likely changepoints in a computationally efficient way. It has good theoretical guarantees and can detect changepoints in real-time. BOCPD is another online method that uses a Bayesian approach to estimate the probability of a changepoint at each time step, making it effective in detecting sudden changes in the data.

According to van den Burg and Williams11, these three CPDs were identified as top performers in a comparison in a general application. The comparison was based on criteria such as $F1$ scores and Segmentation covering metric. We chose these CPDs for their respective advantages and suitability for detecting changepoints in social networks, which can have abrupt changes over time.

To detect changepoints in social networks, we follow a five-step approach. First, we identify the key effects that drive social interactions in the specific network, such as gender and inertia, etc. Next, based on our knowledge of the network, we select an appropriate window length and overlap for analyzing the event history of the network, for instance, a window length of 2000 seconds with a $\frac{2}{3}$ overlap. In the third step, we fit the MW-REM to the event history then extract the effect parameters (β_p) for each fitting window of each effect. Finally, we apply changepoint detection algorithm to the effect parameters of each effect to identify potential changepoints of the certain effects throughout the social network. The algorithm for this process is summarized in Algorithm 1.

Algorithm 1 MW-REM CPs Detection

1: **Input:** A REH data
2: Select the effects that drive social interactions
3: Select an appropriate window length and overlap (e.g., 2000 seconds with $\frac{2}{3}$ overlap)
4: Fit the MW-REM model to the given REH
5: Extract the parameter (β_p) of each effect from each window's REM: $\log \lambda(s, r, t) = \sum_p \beta_p x_p(s, r, t)$.
6: Apply changepoint detection methods to each effect's parameters to identify potential changepoints
7: **Output:** Potential changepoints for each effect in the social network

The fundamental mechanisms of the three CPDs are presented in the following sections.

2.2.1. *Binary Segmentation (BS)*

BS is the most commonly used CPD in many research areas. BS recognizes the changepoints by computing the time point in the data that minimizes the given cost function, then divides the data into two segments by it(i.e., the location of the changepoint), after which the same procedures are performed in each separated sub-segment until no changepoint is left in each segment [20].

In changepoint detection, the cost function is a quality measure that splits the data into segments. CPD is designed to segment the data at the time point where the cost function is minimized. The most common cost function for multiple changepoint detection is [20]:

$$\sum_{i=1}^{m+1} \left[C(y_{(\tau_{i-1}+1):\tau_i}) \right] + \beta f(m) \tag{4}$$

, where i denotes the order of a time point in a segment, m indicates the number of changepoints, τ_i implies the location of a possible changepoint (i.e., time point i). And the m changepoints will divide the data into $m+1$ segments, with the ith segment contains $y_{(\tau_{i-1}+1):\tau_i}$. C represents the cost function of a segment, $\beta f(m)$ serves as a penalty to prevent overfitting.

For BS, the recognized changepoints of the data are required to meet the criteria:

$$C(y_{1:\tau}) + C(y_{(\tau+1):n}) + \beta < C(y_{1:n}) \tag{5}$$

BS continues to search for possible changepoints until there is no τ that meets the criteria, then BS stops.

2.2.2. Pruned Exact Linear Time (PELT)

The PELT is a method based on the Segment Neighborhood changepoint detection method (SN)[5]. SN employs dynamic programming to scan the entire segmented area. It first establishes the maximum number of changepoints, next evaluates the cost function of all possible segments. Eventually, the number of changepoints of the data is between 0 and the previously set maximum number. Further, the SN is capable of including any form of penalty(i.e., $\beta f(m)$), yet with the drawback of high computational cost.

The PELT solves the high computational cost of SN whilst maintaining the accuracy of identifying changepoints. It improves computational efficiency by removing the value of τ from each iteration that is unlikely to be the minimum value, simultaneously searching for the value of τ that minimizes the cost function below [20]:

$$\sum_{i=1}^{m+1} \left[C(y_{(\tau_{i-1}+1):\tau_i}) + \beta \right] \tag{6}$$

, which is equivalent to (4), where $f(m) = m$. The PELT considers the cost function of all potential segments, which ranges between 0 and the previously set maximum number of changepoints, and stops when no more changepoints are detected.

2.2.3. Bayesian Online Changepoint Detection (BOCPD)

Unlike BS and PELT, which rely on cost functions to identify changepoints, BOCPD infers changepoints based on Bayesian approach, which define changepoints in terms of posterior probabilities (i.e., run length probabilities) at time points.

In BOCPD, run length is an essential concept, it represents the length of time points elapsed since the last identified changepoint, which can be understood as akin to the segments in PELT and BS. Whenever BOCPD recognizes a changepoint, the run length drops to 0 and recalculates the length. To determine the changepoints, BOCPD is required to calculate the run length probabilities (i.e., posterior probabilities) for each time point. Given that each time point contains probabilities of increase and decrease in run length, the run length probabilities thus includes both growth probabilities and changepoint probabilities. According to Adams and Mackay[1], to save computational costs, it is suggested to set a cut-off point for the run length probability, typically 10^{-4}, where if the run length probability reaches such cut-off point, the time point is determined as a changepoint.

Overall, the BOCPD starts by building the predictive distribution from the potential locations of changepoints, which reveals any prior knowledge regarding the data generation process. Then, based on the given predictive distribution, the BOCPD computes the run length probability at a time point, with new data coming in, the predictive distribution is continuously updated, the BOCPD iteratively runs the same procedure until no new data appear.

2.3. *Generation of synthetic REH data*

To evaluate the effectiveness of our proposed changepoint detection approach for REH data, we generated synthetic datasets with various changepoint settings. For each setting, we created 15 datasets that were simulated based on the MW-REM characteristics. These synthetic datasets were constructed using a social network consisting of 30 actors and 10,000 events.

To construct these datasets, we randomly selected two exogenous effects and two endogenous effects from the most common ones. We then specified the parameter values (β_p) for each effect and its changes over time. The assignment of the effects' parameters in the synthetic data is based on Meijerink-Bosman's [22] with slight adjustments. The exogenous effects include the "Sender effect," which represents the actor's exogenous attributes that impact their event sending rate, and the "Difference effect," which indicates the difference in personal attributes that influence the rate of sending events. The endogenous effects consist of the "Inertia effect," which describes the tendency of actors to repeatedly select the same receiver for their events, and the "Outdegree of the Sender effect," which indicates the inclination of actors to send events if they have previously sent more events.

Using the assigned parameters of the effects, each sender-receiver pair (s, r) in the risk set R obtained the probability of occurrence at every event, as shown in Equation 1. We then built the REH by selecting the (s, r) pair with the highest probability at each event. In this study, we designed five different changepoint settings for the REH data, each of which we simulated 15 datasets:

(1) The REH without changepoints.
(2) The REH has 1 changepoint in the inertia effect, but not for the rest.
(3) The REH with 1 changepoint in all effects.
(4) The REH with 2 changepoints in the inertia effect, but not for the rest.
(5) The REH with 2 changepoints in all effects.

For the datasets with the 1 changepoint setting, we set the changepoint at $t = 38200$ second for the effect(s) parameter. For the datasets with the 2 changepoints setting, we set the changepoints at $t = 16750$ second and $t = 53900$ second for the effect(s) parameters.

2.4. *The effectiveness and performance of CPDs*

Having generated synthetic REH data with different changepoint settings, we proceeded to evaluate the effectiveness of our proposed changepoint detection approach on these datasets. To this end, we fitted the MW-REM with a window length of 2000 seconds and $\frac{2}{3}$ overlap to each dataset and extracted the effects' parameters. In the following section, we describe how we inspected the performance and compared three changepoint detection algorithms applied to these extracted parameters, utilizing three metrics: the confusion matrix, mean squared error (MSE), and mean signed difference (MSD).

2.4.1. *Confusion matrix*

After feeding the changepoint detection algorithms with the effects' parameters, we used the confusion matrix to evaluate the performance of each algorithm for each effect. A true positive indicates that the algorithm correctly detected a window containing the changepoint of the effect. Notably, due to the overlapping property of the windows, a changepoint can be contained in three consecutive windows simultaneously. Therefore, if an algorithm detects the changepoint in any of the three windows, it is considered a true positive. However, since the synthetic datasets are produced based on selecting the (s, r) pair with the highest rate probability in the risk set R for every event, the locations of the changepoints may differ slightly from our assignment. As a result, if a changepoint detection algorithm detects a changepoint within the range of three windows of the windows containing the true changepoint, we consider it a true positive.

A false positive indicates that the algorithm falsely detected a window as a changepoint, while a false negative indicates that the algorithm failed to detect a window containing the changepoint of the effect. However, our synthetic datasets are highly imbalanced, with many windows and few changepoints, so we did not take the true negative into account. Table 2 presents the confusion matrix for changepoint detection, showing the actual and predicted changepoints and non-changepoints.

	Actually Changepoint	*Actually Not Changepoint*
Predicted Changepoint	True Positive	False Positive
Predicted Not Changepoint	False Negative	

Table 2.: Confusion Matrix for changepoint detection

Given the information from the confusion matrix, we employ three indicators to assess the effectiveness of our proposed approach and the performance of the three changepoint detection algorithms in detecting changepoints in REH. The first indicator is the number of false positive cases. We separately sum the number of false positives of the effects with no changepoint, one changepoint, and two changepoints for each changepoint detection algorithm. For instance, if the REH has one changepoint in the inertia effect, but not for the other effects, the number of false positives of the inertia effect by a changepoint detection algorithm is summed in the one changepoint group, while the rest of the effects are summed in the no changepoint group. This is done to determine which of the three changepoint algorithms has the highest likelihood of falsely detecting a changepoint when there is none, considering the no changepoint, one changepoint, and two changepoints settings for each effect.

The second indicator is the true positive rate (TPR). Similar to the false positives indicator, we separate the effects into groups based on their number of changepoints. However, since there are no true positives for the effects with no changepoint, we only consider the groups with one and two changepoints for each changepoint detection algorithm. The TPR is calculated as follows:

$$TPR_g = \frac{TP_g}{TP_g + FN_g} \tag{7}$$

, where TP indicates the number of true positive cases, FN indicates the number of false negative cases, and g indicates the changepoint group. Through the TPR, we obtain information about the probability that each changepoint detection algorithm correctly predicts the true positive for the effects with one or two changepoints, respectively, among all positive observations.

The third indicator is the positive predictive value (PPV). Similar to the TPR and false positives indicators, we also group the effects into one changepoint and two changepoint groups based on their number of changepoints. The PPV is calculated as:

$$PPV_g = \frac{TP_g}{TP_g + FP_g} \tag{8}$$

, where TP represents the number of true positive cases, FP represents the number of false positive cases, and g represents the changepoint group. The PPV indicates the probability that a predicted changepoint is indeed a changepoint, providing insight into the precision of the changepoint detection algorithms.

2.4.2. Mean Squared Error (MSE) & Mean Signed Difference (MSD)

To evaluate the performance of each changepoint detection algorithm, we use mean squared error (MSE) and mean signed difference (MSD) as measures to examine the accuracy of the predicted changepoint window and the tendency of the algorithm to detect changepoints early or late.

The MSE measures the average squared distance between the predicted and actual changepoint windows for each changepoint detection algorithm. We compute the MSE only for true positive cases from the confusion matrix of each effect. Specifically, we calculate the MSE as follows [3]:

$$MSE = \frac{\sum_{i=1}^{\#CP}(Predicted(CP) - Actual(CP))^2}{\#CP} \tag{9}$$

,where CP denotes the windows containing a changepoint, and $\#CP$ represents the number of changepoints in the REH. The lower the MSE, the higher the precision of the algorithm. To evaluate the performances of the changepoint detection algorithms across different changepoint scenarios, we group the effects into one-changepoint and two-changepoint groups and report the average MSE of each group for each algorithm using the following formula:

$$Avg.MSE_g = \frac{\sum_{i=1}^{N_g} MSE_i}{N_g} \tag{10}$$

, where $Avg.MSE_g$ represents the average MSE for group g, MSE_i is the MSE value for the ith effect in group g, and N_g is the number of effects in group g.

The MSD, on the other hand, is used to examine the tendency of the changepoint detection algorithm to detect changepoints early or late. We compute the MSD only for true positive cases from the confusion matrix of each effect. Specifically, we calculate the MSD as follows:

$$MSD = \frac{\sum_{i=1}^{\#CP}(Predicted(CP) - Actual(CP))}{\#CP} \tag{11}$$

, here, a negative MSD indicates that the changepoint detection algorithm tends to predict the changepoint window earlier than the true changepoint window, while a positive MSD indicates that the algorithm tends to predict the changepoint window later than the true changepoint window.

To evaluate the changepoint detection algorithms' detection tendencies under different changepoint scenarios, we group the effects into one-changepoint and two-changepoint groups. The average MSD of each group for each algorithm is reported using the following formula:

$$Avg.MSD_g = \frac{\sum_{i=1}^{N_g} MSD_i}{N_g} \tag{12}$$

, where $Avg.MSD_g$ represents the average MSD for group g, MSD_i is the MSD value for the ith effect in group g, and N_g is the number of effects in group g. This allows us to assess each changepoint detection algorithm's tendency to detect changepoints early or late in both univariate and multivariate changepoints scenarios of effects.

2.5. *Manipulation of real-life Apollo 13 voice-loop data*

The study utilized real-life data from the publicly available Apollo 13 voice loop data, which captured the communication between the astronauts and Mission Control during the failed Apollo 13 mission. This mission aimed to land on the Moon, but a routine agitation of one of the oxygen tanks caused an explosion that damaged the wire insulation inside, resulting in the discharge of the contents of both oxygen tanks. This left the astronauts without systems to generate electricity and oxygen, prompting them to contact Mission Control for assistance, and ultimately leading to the cancellation of the mission. The analyzed data covers the period from one hour before the emergency until Apollo 13 was safely back on a trajectory towards Earth, specifically from 54:46:28 to 62:06:53 (hh:mm:ss) of the mission timeline.

In the Apollo 13 voice loop data, a pivotal moment occurred when an astronaut stated, "Houston, we've had a problem here," at 55:54:53. This moment marks the start of the emergency, and we have selected it as the location of the changepoint in our study. We hypothesize that the old interaction patterns were disrupted after this point, making it an ideal location to test the effectiveness of our proposed changepoint detection approach on a real social network.

To apply our proposed changepoint detection approach (see Algorithm 1), we selected several effects that have a relationship with the network. These effects include the "Inertia effect," which refers to the tendency for actors to repeatedly interact with each other, the "Outdegree of the sender effect," which refers to the tendency for actors to send events if they have sent more past events, the "Indegree of the receiver effect," which refers to the tendency for actors to receive events if they have received more past events, and the "Total degree of the sender effect," which refers to the tendency for actors to send events if they have sent and received more past events. We also selected three other effects that capture specific patterns of interaction: the "AB-BA pshift," which refers to the tendency for immediate reciprocation, where the next sender is the current receiver and the next receiver is the current sender, the "AB-XA pshift," which refers to a tendency for turn usurping, where the next sender is not in the current event and the next receiver is the current sender, and the "AB-BY pshift," which refers to a tendency for turn receiving, where the next sender is the current receiver and the next receiver is not in the current event.

Considering the findings of Meijerink-Bosman's research [23], we decide to fit the MW-REM with a 1000-second window length and $\frac{2}{3}$ overlap, as it provided a good insight into the dynamic of the social network. We then apply this window setting to the Apollo 13 voice loop data, extract the parameters of each effect along the windows, and feed them to the three changepoint detection algorithms employed in our study.

In an ideal situation, by feeding the parameters of the effects to the changepoint detection algorithms, they could successfully detect the presence of changepoints for each effect in the MW-REM, around or precisely at the windows that contain the message reporting the issue.

3. Results

3.1. *Synthetic REH datasets*

3.2. *Real-life Apollo 13 data*

4. Discussion

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